Air Traffic Performance by Market Segments

Dipasis Bhadra[1]
Center for Advanced System Development (CAASD)
The MITRE Corporation
7515 Colshire Avenue
McLean, VA 22102

ABSTRACT

How is air traffic performance affected by type and location of markets? Is there any pattern to how air traffic performs with respect to the size of the markets? How does the type of aircraft affect performance? How sensitive are performance measures with respect to types of networks? How does performance change, on average, from one season to another? How does performance change when we account for industry structure?

The National Airspace System (NAS) in the United States is structured primarily around a web of air transportation markets linking each other through a network of 465 commercial airports located in and around 363 metropolitan statistical areas (MSAs). The total number of origin-destination (O&D) markets in the NAS ranges somewhere between 36,000 – 40,000 pairs depending upon seasons and economic cycles. In its present structure, these markets are hierarchical; a small number of markets accounts for the largest number of passengers and, hence, air traffic flows. For example, there were approximately 105 markets (0.3% of the total) which had 1,000 or more passengers a day (i.e., thick markets), but these accounted for almost 17% of the total passengers. On the other hand, there were almost 28,000 markets (78% of the total) with 10 or fewer passengers a day that accounted for only 6% of total passengers in 2003.

Traffic flow from markets and segments (i.e., T100 market and T100 segment of Form 41, respectively) are the primary data used for this paper. Using the T100 market and segment data from 1996 to 2003), we build well-specified econometric models to estimate and evaluate performance measures defined over market segments and networks. This econometric framework establishes and evaluates empirical linkages between performance measures (i.e., delays constructed using time from ramp-to-ramp against time airborne) and size of the markets, locations, distance, seasons of the year, aircraft type, and industry competitiveness over time. Preliminary estimates indicate that size of market, type of aircraft, and distance play important roles in influencing performance measures.

---

1 Author is a Principal Economist. Paper will be presented at the 4th Annual Technical Forum of the ATIO/AIAA, Chicago, IL, during September 20-23, 2004.

Air Traffic Performance by Market Segments

I. Introduction

The National Airspace System (NAS) in the United States is structured primarily around a web of air transportation markets linked through a network of 465 commercial airports located in and around 363 metropolitan statistical areas (MSAs). The total number of origin-destination (O&D) markets in the NAS ranges somewhere between 36,000 – 40,000 pairs depending upon seasons and economic cycles. These markets are hierarchical; a smaller number of markets account for the largest number of passengers and, hence, air traffic flows. For example, there were approximately 105 markets (0.3% of total) which had 1,000 or more passengers a day (i.e., “thick” markets), but these accounted for almost 17% of total passengers. On the other hand, there were almost 28,000 markets (78% of total) with 10 passengers or less a day that accounted for only 6% of total passengers in 2003.

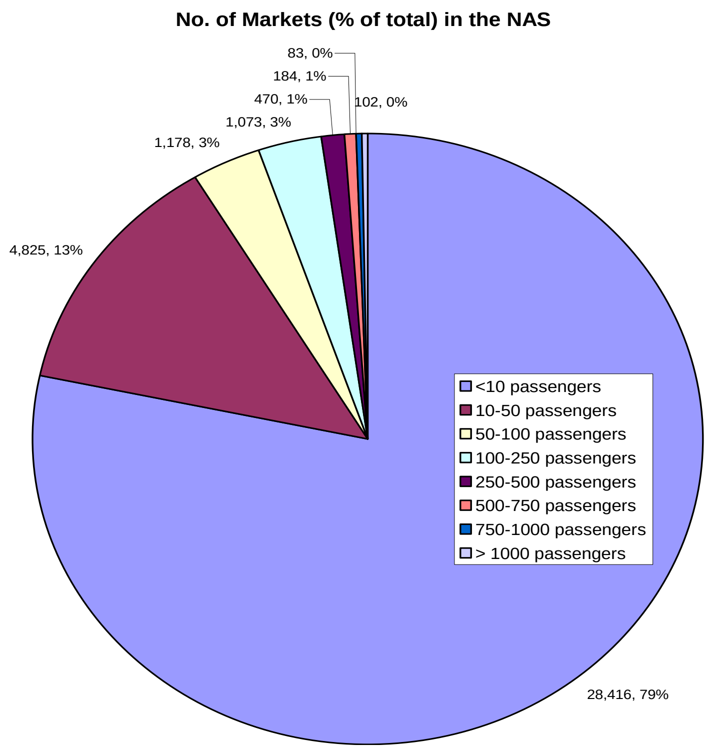


Figure 1: Number of Markets by Market Segments

A majority of these markets (73 – 80%) are “thin” in size, (meaning they carry fewer than 10 passengers a day), followed by markets that carry 10 – 50 passengers a day (0.13 – 0.17%) (see Figure 1). In comparison, “thicker” markets (i.e., 100 or more passengers a day) are relatively small, numbering somewhere between 1,900 – 2,200 during the period 2000 – 2003 with a relatively stable share of 5 – 6% of the total market. Interestingly, however, the share of the market in total passengers is asymmetrical. “Thick” markets carried somewhere between 66 – 90% of all passengers while “thin” markets carried only 16 – 18% of all passengers during the period 2000 – 2003 (see Figure 2).

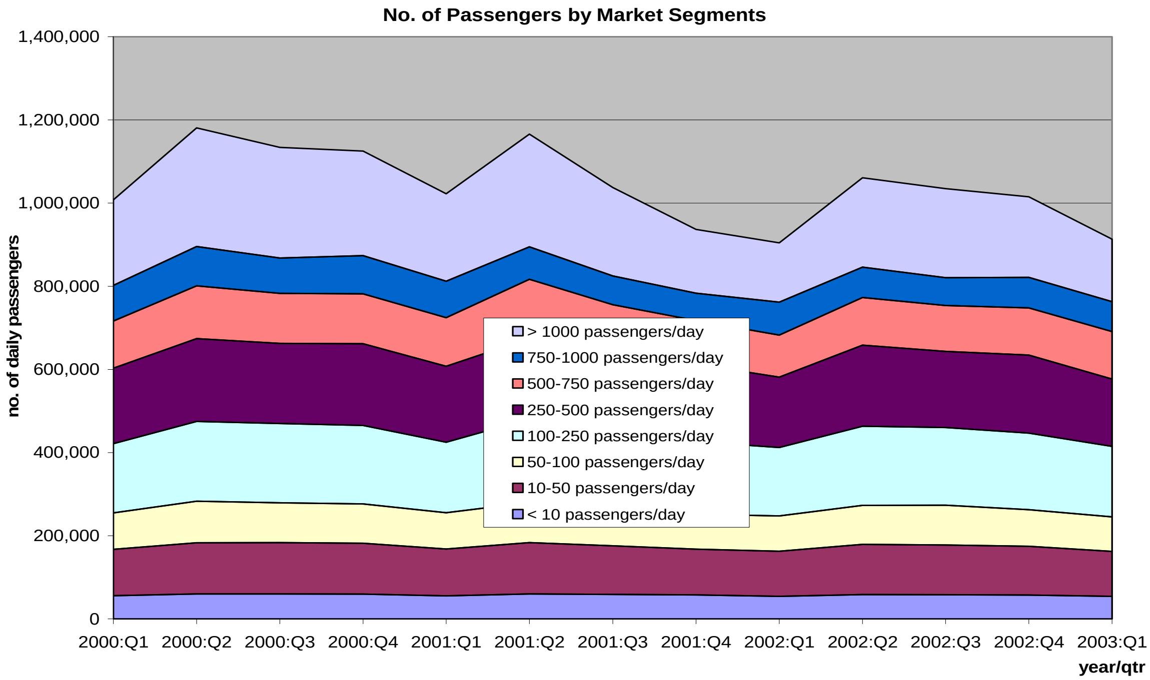


Figure 2: Number of Passengers by Market Segments

Many of the thin markets are economically infeasible for commercial air service [see GAO (2002); Bhadra (2004)]. Lack of volume in passengers makes them unattractive as stand-alone markets.[2] Hence, many of these markets are served as a point in the commercial air carriers' hub-and-spoke network.[3] These spokes, or points, are critical for the viability of the hub-and-spoke network, which evolved as the dominant form of the air transportation network, following the deregulation of the industry in 1978.

Figure 3 demonstrates the hierarchical nature of the hub-and-spoke network in the United States (US) air transportation industry. Air transportation between hubs (i.e., between the top 35 commercial airports, also known as the Operational Evolution Plan (OEP) airports) cover almost 50% of total passengers followed by those between hub and spokes with a share ranging between 45 – 48%. In comparison, point to point travel had a share of around 5 – 6% of total number of passengers.

---

2 An acceptable "rule-of-thumb" for commercial feasibility requires daily O&D passengers of 75 – 100 a day. This may require 1 – 2 services a day using either turbo-prop or regional jet (RJ) service.

3 Strictly speaking, hub-and-spoke networks can be defined to include hub-to-hub and hub-to-spoke travels. In comparison, a point-to-point network consists of travel between two non-hub airports (for more details on these definitions and econometric-time series model, see Bhadra and Texter , 2004).

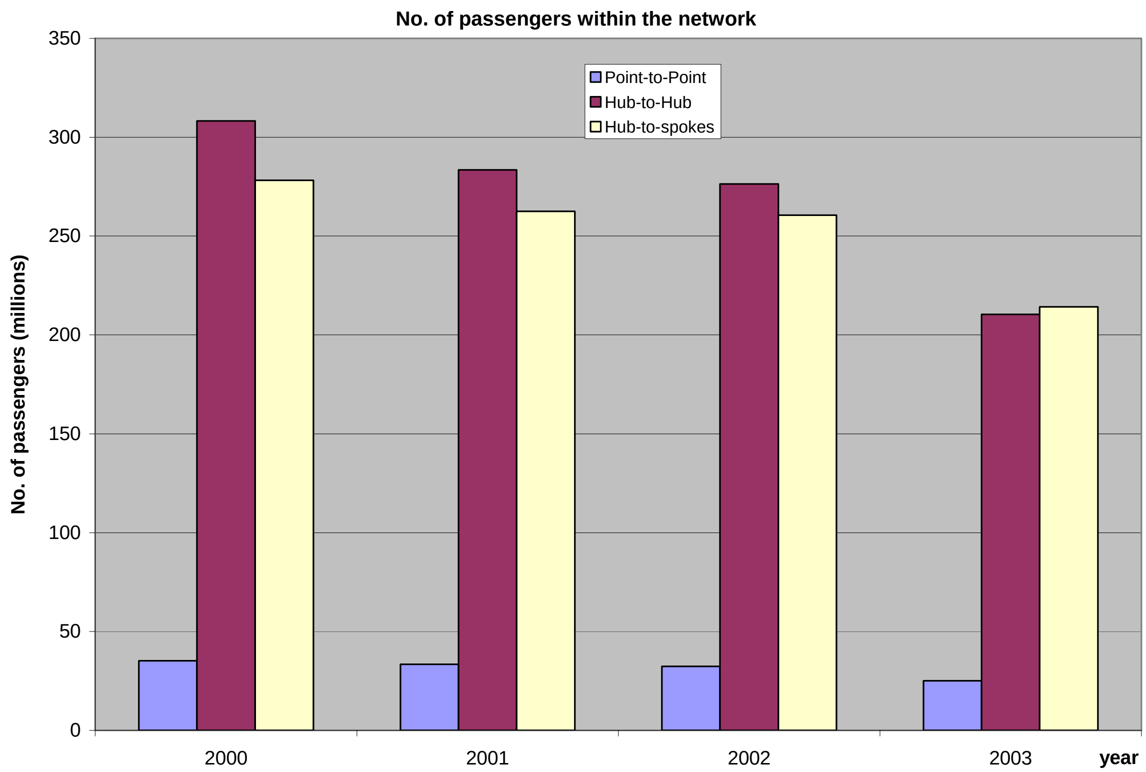


Figure 3: Number of Passengers by Types of Network

While the connectivity through a hub-and-spoke network has brought geographic proximity and economic prosperity to many of the small communities, it has brought some unavoidable consequences as well. Primary among them are the delays associated with air travel that is passed onto these small communities from those that they are connected with. It is well known [FAA (2004)] that delays in air transportation are heavily concentrated in airports that are primarily large hub airports. Large hubs are also connected to a larger number of spokes.[4] Thus, as large hubs experience delays in air transportation, they cascade through the system onto the spokes. Hence, it is likely that the spoke airports that are connected to large hub airports through a hub-and-spoke system may bear a relatively larger proportion of these delays compared to those that are not. Furthermore, the larger the extent of these connections, the more intense the effect will be on the system. Hence, the delays at Chicago's O'Hare (ORD) are likely to impact the nation more severely than other airports[5]. It is also likely that the extent and intensity

4 For example, Chicago's O'Hare International Airport (ORD) connects to 174 airports (both hub and spokes) compared to Dallas Fort-Worth International Airport (DFW) 164, John F. Kennedy International Airport (JFK) 146, and Denver Stapleton Airport (DEN) 133 destinations. In comparison, fewer connections are offered at relatively smaller airports: Philadelphia International Airport (PHL) has 112 connections, while Baltimore-Washington International Airport (BWI) and Chicago's Midway Airport (MDW) offered 74 and 63 connections for a representative first week of August 2004 from the official airline guide (OAG). While the number of departures, and thus passenger flows, are relatively more in the thicker markets, smaller or thinner markets are linked to the system through the complex scheduling that places dominance to the larger hubs and their links to other thick markets.

5 In the month of August 2004, the Federal Aviation Administration (FAA) brought together all carriers serving ORD to voluntarily accept capacity limits in peak hour operations. This is the third attempt during the last year to solve the excessive delay problems at ORD. In describing the problem, the FAA Administrator stated "As Chicago goes, so goes the system" because when ORD gets jammed, controllers delay takeoffs at other

of these delays would be influenced by the type of hubs. For example, if a hub is dominated by one carrier (a so called *"fortress" hub*), the impact of delays on spokes may be different than if it was served by two or more carriers. The extent of delays at airports that are connected by a point-to-point network, as opposed to those connected by a hub-and-spoke system, is expected to be different as well.

This paper is an attempt to understand the air traffic performance by market segments. In particular, we ask the following questions: How does the air traffic performance behave by type of market segment, and type of network? Can the performance patterns be explained by systematic factors, e.g., time of the year and/or by market factors such as volume and type of passengers and type of air carriers? To what extent do these patterns depend on type of aircraft serving these markets? The paper is organized as follows: Section II defines air traffic performance measures and provides data with regard to its trends over time and by different categories. Section III introduces the data and postulates the key empirical hypotheses. Section IV discusses the empirical findings of the study. Finally, Section V offers some conclusions.

II. Definition of Performance Criteria[6]

Two measures that are often used to evaluate operational performance of aircraft, and air carriers and the airspace system in turn, are time from ramp-to-ramp[7] and airborne time (see Bolzack, et. al., 1997 for standard definitions). Ramp-to-ramp time is computed from the moment an aircraft first moves under its own power for purposes of flight, until it comes to rest at the next point of landing. The airborne hours is computed from the moment an aircraft leaves the ground until it touches the ground at the end of a flight stage. Thus,

Ramp-to-ramp time = taxi-out time + airborne time + taxi-in time

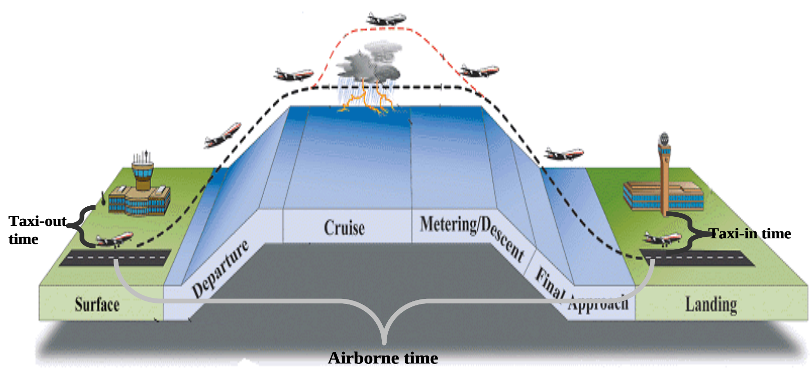


Figure 4: Taxi-out, Airborne, and Taxi-in Time

---

airports to give ORD time to clear out its backlog (see "O'Hare delays hold up whole system; FAA wants it fixed", Associated Press report at http://www.tennessean.com/business/archives/04/08/55430005.shtml; retrieved 8/5/2004).

6 Data for our analysis come from T100 segment files from Form 41. For data on performance criteria including definitions, see also T100 traffic segment data from Form 41 data that are filed by major air carriers (see http://www.transtats.bts.gov/ for more details).

7 For evaluating operational efficiency, an aircraft's movement is tracked from the moment it moves on its own power. However, airlines often have control over ramps leading onto taxi-in and out phases, thus impacting the efficiency. In order to account for that effect, distinctions are made sometimes between gate-to-gate and ramp-to-ramp. Furthermore, these differences are systematic (i.e., for larger airports) and insignificant for smaller airports. For our analysis, we do not make distinctions between these two measures.

Poor performance can be classified into strict categories according to taxi out delays (e.g., those arising from queues, ground delays, and ground stops), airborne delays (e.g., those arising from holding in the airspace due to bad weather or unavailability of landing space), and taxi in delays (i.e., queues and congestion at the airport, apron, and gate). For reasons of cost and safety, airborne holding does not happen frequently. Most delays occur on the ground, either at the taxi out or at the taxi in phase. The higher the ratio of airborne time to ramp-to-ramp time, higher the efficiency of the flight. Our performance criterion is thus defined as the ratio of airborne to ramp-to-ramp time, with lower and upper limits approaching 0 and 1, respectively.[8]

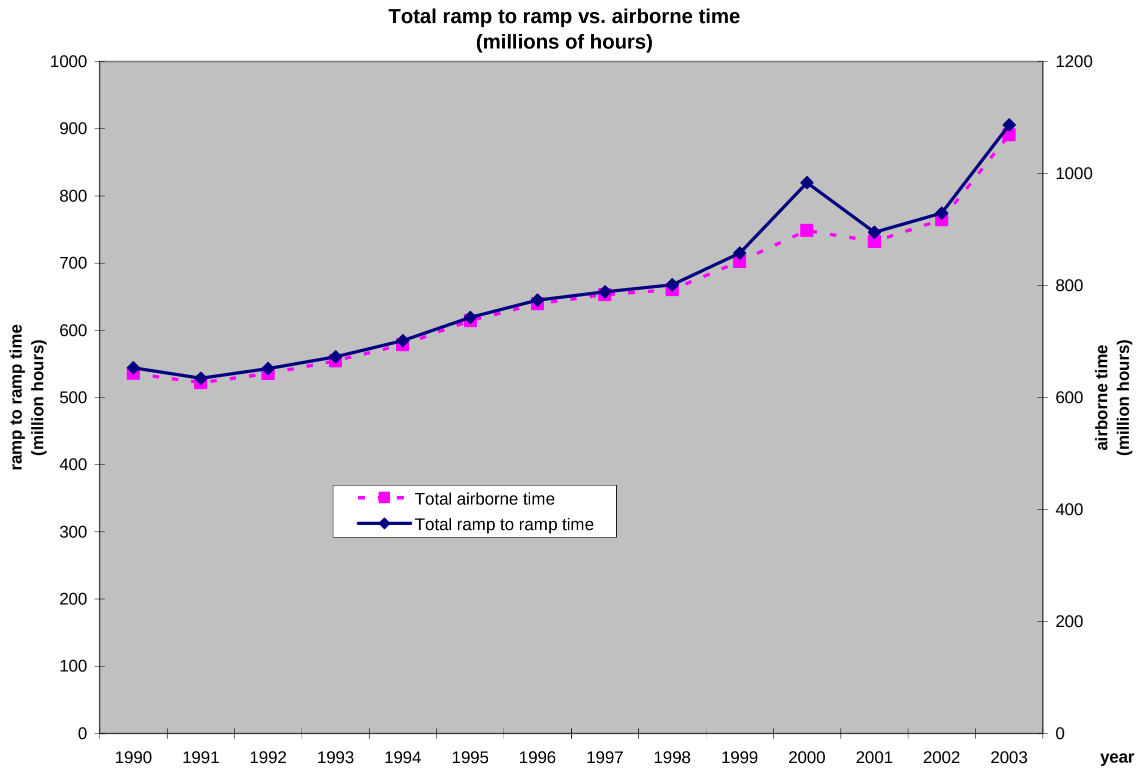


Figure 5: Trends in Ramp-to-Ramp and Airborne Time

Figure 5 clearly demonstrates that NAS utilization is increasing over time. The annual growth rate in the early to mid 1990s was approximately 3%, with both ramp-to-ramp and airborne hours tracking quite closely to each other. This was followed by an accelerated growth period (1999 – 2000) where the airborne hours grew at an annual growth rate of 6%, while ramp-to-ramp time grew at an annual rate of 11%. This imbalance is likely contributed to a degrading of air transportation performance. The period of 1999 to 2000 is widely known for high delays in air transportation. Symmetrically, the downward adjustment in ramp-to-ramp hours, following September 11, 2001 (9/11), has been far more dramatic (-9%) than the downward adjustment in airborne hours (-2%) suggesting that a large part of this adjustment in NAS utilization may have come from adjusting for performance. Finally, there are some seasonal variations in the data as well.

8 It is obvious that the ratio can never attain either value of 1 or 0 at the limit, since taxiing in and out will always be positive fractions of total ramp-to-ramp time.

Controlling for O&D and distances, the higher the ratio of airborne to ramp-to-ramp, (i.e., index value closer to one), the more efficient the flight is. That is, the higher the percentage of time in the air, *ceteris paribus*, the higher the overall productivity of the aircraft and, hence, the higher the positive impact on air carrier profitability. Technical aircraft superiority (i.e., climbing rate and cruising speed) also influences performance and may impact air traffic delays negatively [see Cavcar and Cavcar (2004) for an analysis on technical specifications of aircraft and their impact on air traffic delays]. The cost efficiencies of an air carrier arise from minimizing these delays, in part, by maintaining the overall performance throughout the system including the aircraft efficiency. An example of this accomplishment is cited consistently by the experience of Southwest Airlines. Southwest Airlines, on average, has a faster turn-around time than any other air carrier and, hence, is likely to attain higher airborne time, vis-à-vis ramp-to-ramp time (see Figure 6).

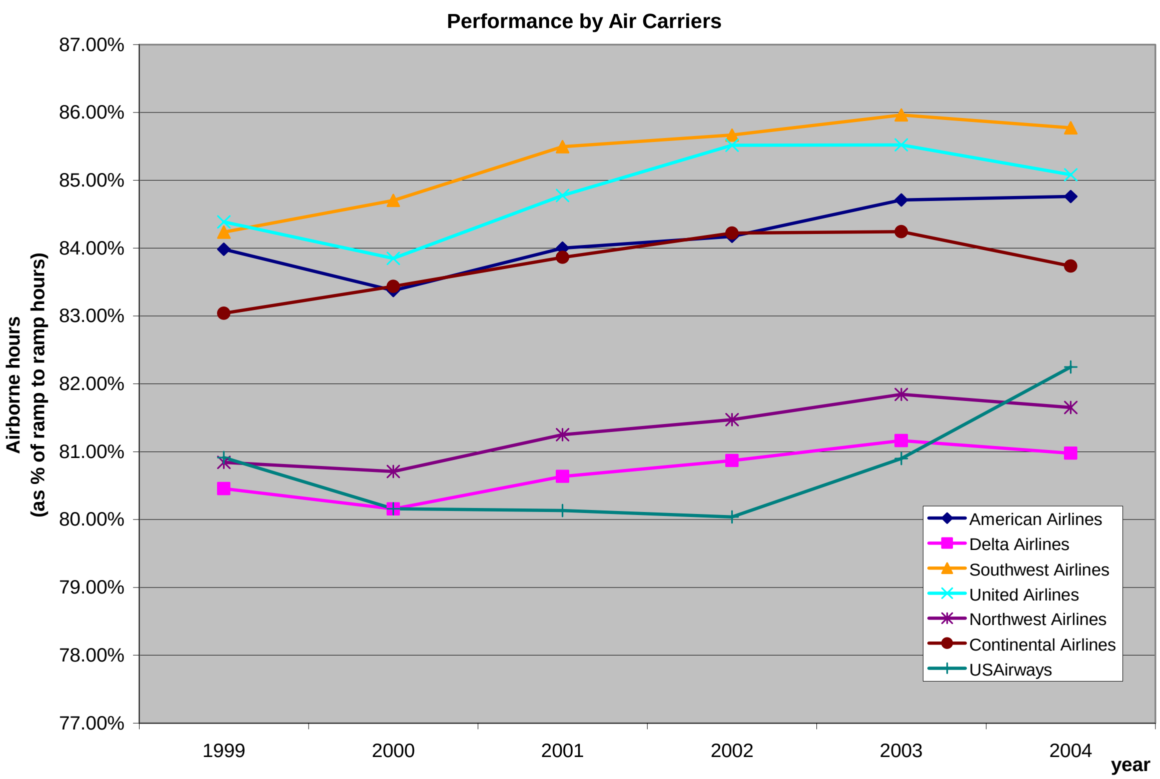


Figure 6. Air Traffic Performance by Air Carriers

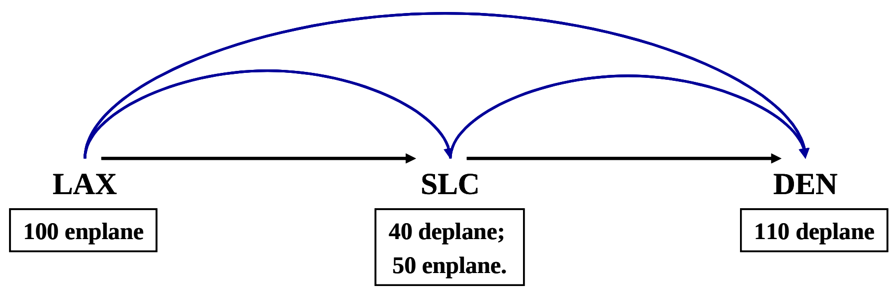
The evaluation of system performance using delay as the chief criterion has often been used to account for the economic losses [Bolczak et. al., 1997]. Eurocontrol (2000) estimates the annual losses stemming from air traffic control delays to be approximately € 5.73 billion; $2 billion from longer trajectories arising from flying fixed airways network, and $10 billion due to air traffic control actions generating deviations from optimal aircraft flight profiles [see also Dell'Olmo and Lulli, 2002]. Clearly, delays have serious economic consequences.

III. Data and Empirical Hypotheses

Data for this exercise comes from the Bureau of Transportation Statistics/Department of Transportation's (BTS/DOT) T100 schedule. T100 is the transportation schedule of Form 41 data that every major airline is required to submit to the DOT every quarter (for more details, see http://www.transtats.bts.gov and use the aviation data link for T100 domestic data segments in Form 41 traffic file). T100 is broken into two parts: T100 market segment (T100M), which covers all the O&D markets and the T100 segment (T100S) which provides data for market segments serving O&D markets. In particular, T100S is the Data Bank 28DS of Form 41 that provides segment traffic (i.e., the number of passengers and departures scheduled and performed) by scheduled air carriers, freight, mail, service class, type of aircraft equipment, capacity (i.e., available capacity payload and available capacity seats), performance indicators (i.e., ramp-to-ramp elapsed time, airborne elapsed time), distance, month, and year. The data are reported by major air carriers operating between airports located within the boundaries of the US and its territories [see USDOT, 2001 for more details] and are presently available for January, 1995 – May, 2004 [see http://www.transtats.bts.gov for more details]. For our empirical analysis, we use T100 domestic segment quarterly data for the period covering 1995: first quarter (Q1) – 2003: third quarter (Q3), 35 continuous quarters.

T100 data can be best explained in Figure 7 [USDOT, 1992]:

Flights from LAX to SLC to DEN



<u>Non-Stop Segments</u>: Represented by straight arrows above, i.e., number of passengers transported between points, (between take-off and landings).

LAX to SLC: 100 passengers transported;
SLC to DEN: 110 passengers transported;

<u>On-Flight Markets</u>: Represented by curved lines above, i.e., where passengers are enplaned and deplaned on a <u>flight</u> (flight number).

LAX to SLC: 40 passengers;
LAX to DEN: 60 passengers;
SLC to DEN: 50 passengers;

For a one-stop flight, the number of passengers would be the same number under segment and market.

Figure 7: An Illustration of T100 data

For a hypothetical flight between Los Angeles (LAX) to Salt Lake City (SLC) to Denver (DEN), non-stop segments data (T100S) accounts for the transfer passengers, in addition to O&D passengers. T100M, on the other hand, accounts for the number of passengers that are traveling between O&D market pairs only. The T100M captures a limited variables: number of passengers by O&D, freight, mail, carriers, distance, month, and year.

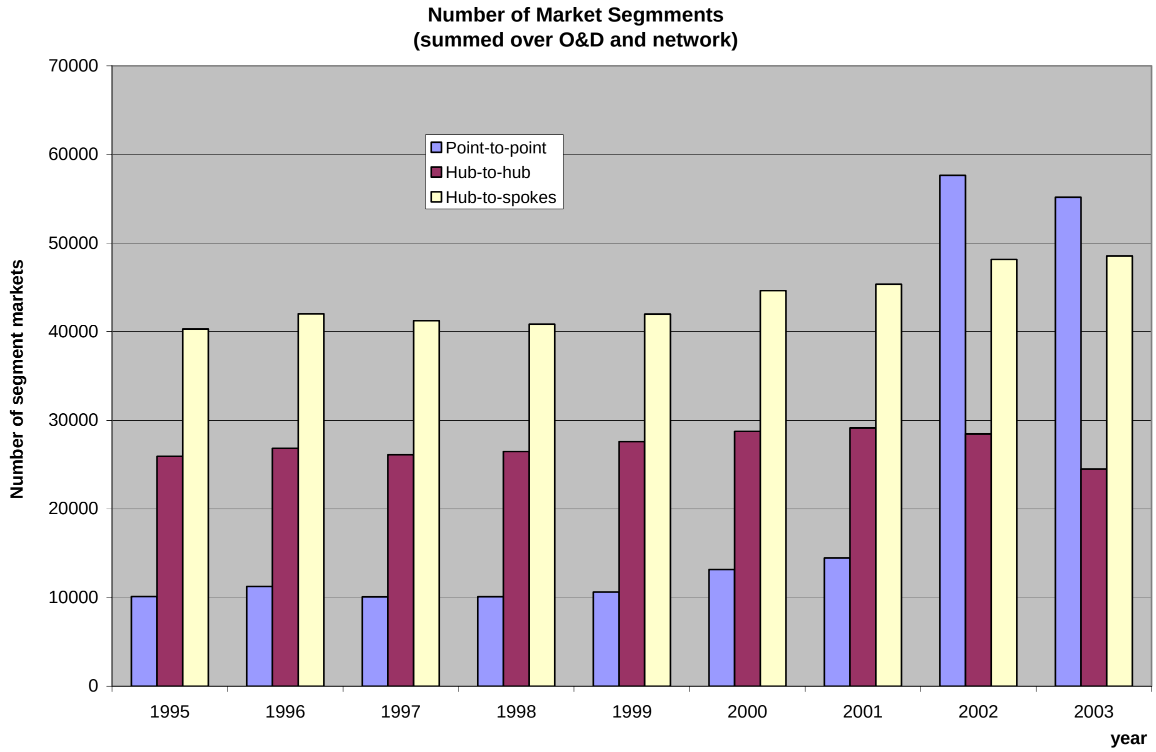


Figure 8: Data for Econometric Estimation

Each segment reported in T100S is unique, distinctly defined by air carrier and equipment type. The same LAX – SLC will be reported twice, for example, if a carrier flew the segment using two equipment types. This phenomenon increases as more carriers crowd in and fly more equipment types, i.e., the market becomes increasingly fragmented. Despite this fragmentation, the total number of segments can be aggregated over O&Ds to provide a logical basis for defining the network. For example, there were 70,127 distinct segments in 2003:Q3. These unique segments reduced to 11,179 O&D segments when summarized by O&D. For 1998:Q3, there were 43,660 distinct segments. Summarizing by O&D yielded 5,874 O&D segments.[9] It is the latter that provides the basis for our analysis in this paper. Summing the distinct 1,910,826 segments over O&D pairs by types of network (i.e., point-to-point, hub-to-hub, and hub-and-spokes) for the period 1995:Q1 – 2003:Q3 result in an aggregate of 829,580 observations. There were 192,647 observations (i.e., number of segments) for the point-to-point network segment, 243,896 observations for the hub-to-hub network segment, and 393,042 observations for hub-to-spoke network segment. These observations have been used for estimation of our econometric model. A breakdown of these observations by year and by network is shown in Figure 8.

We specify the econometric model as follows:

9 During the period 1995:Q1 – 2001:Q4, there were, on average, 43,942 distinct segments per quarter in the dataset. During the period 2002:Q1 – 2003:Q3, the average number per quarter jumped to 66,329 distinct segments. This is due primarily to increased fragmentation of the markets, a direct result of the ongoing restructuring of the industry, led by the expanding services of low-cost carriers and the regional carriers, and retreat of network carriers into their hubs.

$$index^K = F(p_0, p_1(dummy_1), p_2(mktsize), p_3(Terrorism), p_4(Avgdistance), p_5(Avgdistancesquarred)\ p_6(avgseats\ or\ ACCategory), p_{AA}(American), p_{CO}(Continental), p_{DL}(Delta), p_{NW}(Northwest), p_{WN}(Southwest), p_{US}(USAir), p_{UA}(United)) \quad (1)$$

where $index^K$ = performance measure = (airborne time/ramp-to-ramp time) and k= 0, 1, 2 where 0 represents the point-to-point network segment, 1 represents the hub-to-hub network segment and 2 represents the hub-to-spoke network segment; $dummy_1$ = seasonal dummy, where spring and summer = 1 and fall and winter = 0; mktsize = a dummy variable capturing size effects: 0 is thinnest (i.e., less than or equal to 10 passengers a day) while 7 is thickest (> 1000 passengers/day); Terrorism: a dummy variable capturing the effect of tragic events of 9/11, i.e., time following September 11, 2001; Avgdistance: average distance (in statue miles) between segment pairs; Avgdistancesquarred: squared average distance between segment pairs; avgseats: average available capacity seats, i.e., size of the A/C captured; we also use ACCategory dummy (1 being lowest, e.g., Cessnas and Pipers; and 6 being the largest, i.e., wide-bodies) to capture the effect of size; and dummies for airlines presence in the market segments. Thus, American is a dummy variable representing American Airlines' presence in the market segments and similarly for other airlines. Notice here that we use six network carriers (American Airlines, Continental Airlines, Delta Airlines, Northwest Airlines, USAirways, and United Airlines) and the most dominant low-cost carrier, i.e., Southwest Airlines in this analysis. There are numerous other airlines, especially in smaller segments. However, we decided to combine them into categories other than these seven carriers. Thus, they will often be represented by a value of 0 in the dataset.

Given our discussion earlier, we attempt to answer the following research questions:

- How is performance affected by the time of the year? Do the busy seasons reduce air traffic performance?
- How does the size of the market affect performance?
- How has performance adjusted following the events of 9/11?
- Does performance get better as larger distances are covered?
- How does the size of the aircraft affect performance? Does the larger size of the aircraft enhance performance and vice versa?
- How do network carriers compare among themselves, and how do they compare against Southwest Airlines in affecting performance measure?

IV. Empirical Results

We combine time series data (1995:Q1 – 2003:Q3) with a cross-section of elements (e.g., by segments and by network) for our empirical analysis. When time series data are used in regression analysis, it is well known [see Pindyck and Rubinfeld, 1991] that the error term is often not independent through time. Instead, the errors are *serially correlated* or what is commonly called *autocorrelated*. Under these circumstances, the efficiency of ordinary least-squares (OLS) parameter estimates is adversely affected and standard error estimates are usually found to be biased.

The commonly used autoregressive error model corrects for serial correlation in time series models. This procedure can fit autoregressive error models of any order and can fit subset of autoregressive models. In order to correct for serial autocorrelation, we used AUTOREG procedure from SAS (Version 8.2) to estimate our model.

Our specification for the index^K model appears to have good statistical properties for two of the three networks. The model's explanatory power for point-to-point network segment is poor (i.e., independent factors do not explain the variations in the index$^{K=0}$ well). When we ran the maximimum likelihood estimation, other properties, i.e., root mean squared errors, and Durbin-Watson statistics, improved considerably over the OLS methods for all networks.

network=0

Maximum Likelihood Estimates			
SSE	9715.07707	DFE	191432
MSE	0.05075	Root MSE	0.22528
SBC	-27153.781	AIC	-27336.704
Regress R-Square	0.0698	Total R-Square	0.0901
Durbin-Watson	2.0657		

network=1

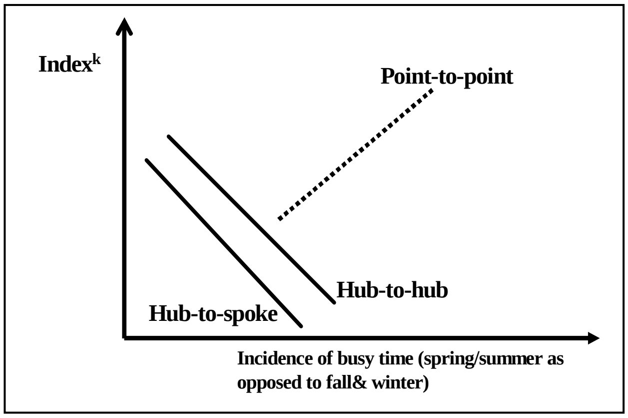
Maximum Likelihood Estimates			
SSE	2924.46878	DFE	242456
MSE	0.01206	Root MSE	0.10983
SBC	.	AIC	.
Regress R-Square	0.3014	Total R-Square	0.4008
Durbin-Watson	2.0015		

network=2

Maximum Likelihood Estimates			
SSE	6891.10251	DFE	390781
MSE	0.01763	Root MSE	0.13279
SBC	.	AIC	.
Regress R-Square	0.2262	Total R-Square	0.3081
Durbin-Watson	1.9948		

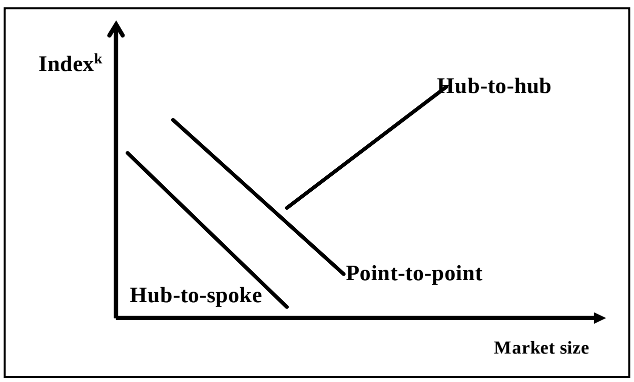
Table 1: Maximum likelihood estimates for the index^K model for different networks

Below, we provide notional summaries and a discussion of our main findings (detailed statistical results have been provided at the Appendix A). Using statistical estimates from Appendix A, notional relationships between air traffic performance (i.e., index^K measured in vertical axis) and the incidence of explanatory variables have been drawn on the graphs. Notice, however, that both magnitudes (i.e., position of one curve vis-à-vis others) and statistical significances (i.e., solid versus dashed lines) of the estimated parameters have also been captured by the graphs. Statistically significant results (i.e., significant for confidence intervals > 99%) are represented by solid lines while results with lower confidence ($\leq$ 99%) are represented by dashed lines.

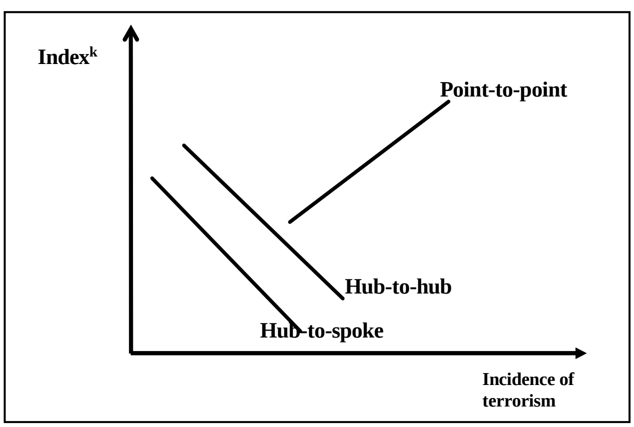


Examining the statistical estimates of the seasonal effect (dummy1) across different networks, we observe that at busier times of the year (i.e., spring and summer), performance degrades for overall hub-and-spoke network segment. In particular, the performance is worse for the hub-to-hub network segment compared to those under the hub-to-spokes network segment as captured by the absolute value of statistical estimates (i.e., -0.008 and -0.002, respectively).

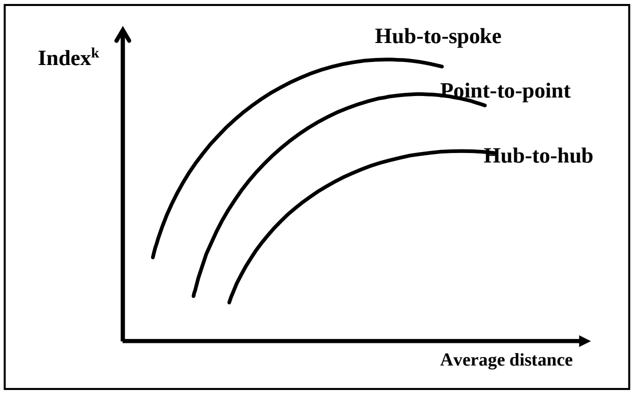
In comparison, busy time appears to improve, *albeit* statistically weakly (confidence intervals of 95%), air traffic performance in the point-to-point network segment. These results may indicate a prevalence of unused capacity in the point-to-point network compared to those under the hub-to-spokes network segment, in general.



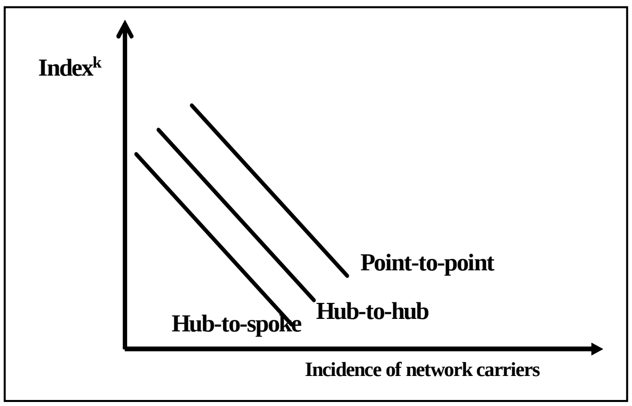
Market size, as captured by the group of dummy variables representing passenger flows, affects networks differently. The larger the size of the market, the better the air traffic performance under the hub-to-hub network segments. In comparison, the point-to-point and the hub-to-spokes perform somewhat poorly as market size gets bigger. These results may indicate that there may be significant positive externalities for market expansion from the hub-to-hub network segment than other types. In other words, there may be unused capacity left in the hub-to-hub network segment with respect to market size.



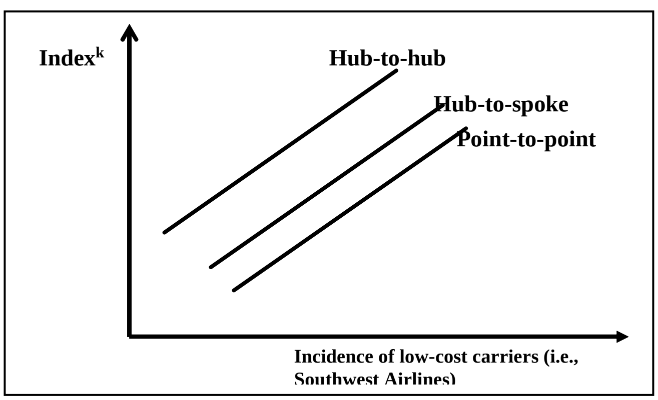
The events following 9/11 seem to have affected networks very differently. For example, while the air traffic performance has markedly improved for the point-to-point network segment, it deteriorated for both the hub-to-spokes and hub-to-hub network segments. Absolute magnitudes of the negative effects indicate that the performance has deteriorated relatively more for the hub-to-spoke network than hub-to-hub following the events of 9/11.



The longer the distances between segment pairs, the more likely it is for air traffic performance to improve. Notice, however, that the improvement slows down (i.e., parameter estimates for squared of distances are negative) with distances. This result is intuitively obvious, since with longer distances, airborne time relative to ramp-to-ramp time increases and, hence, the performance improves. It is obvious that with longer distances both labor and non-labor costs are rationalized improving cost performance as well.

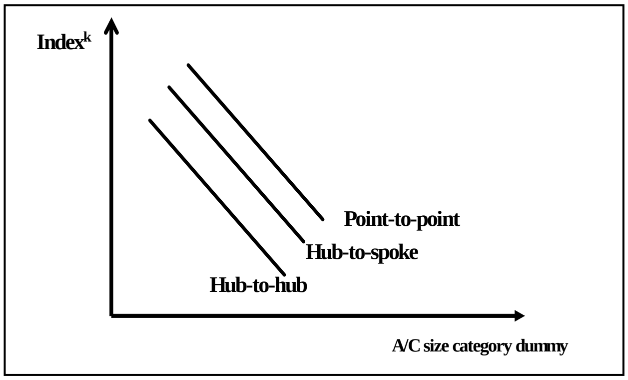


It is interesting to note that the presence of network carriers have a negative impact on air traffic performance, irrespective of types of network. An examination of results (see Appendix A for more details) reveals that the presence of network carriers impacts air traffic performance in point-to-point relatively more than it does to the other two types of networks.



On the contrary, the presence of low-cost carriers, represented by the presence of Southwest Airlines in segment pairs, improves air traffic performances under all networks. Interestingly, the extent and magnitude of this improvement is highest when Southwest Airlines is present in hub-to-hub networks[10] followed by the other two networks. This finding is interesting due to the fact that Southwest has focused its efforts mostly in flying point-to-point routes. The higher performance of Southwest Airlines under hub-to-hub and hub-to-spokes network segments indicates that network carriers may have to worry about quality of services in these markets in addition to traditional fare competition brought on by the carrier.

10 In addition to its primary focus on servicing relatively larger metropolitan areas through secondary airports, Southwest also flies from airports that are designated as hub airports (e.g., Baltimore-Washington (BWI), Phoenix (PHX), Cleveland (CLE), Detroit (DTW), etc.).



Statistical results indicate that the size of the aircraft affects air traffic performance negatively, irrespective of the types of networks. The larger the size of the aircraft, the greater the reduction in air traffic performance. Furthermore, the aircraft size affects the point-to-point network disproportionately more than it does to other two networks. Finally, the lagged autoregressive process indicates that past errors (i.e., four lags) can explain the incidence of air traffic performance fairly well (see Appendix A for more details).

V. Conclusions and Further Research

In this paper, we have developed an empirical framework to examine the determinants of air traffic performance. We the defined performance measure as the ratio of airborne time to total ramp-to-ramp time (index^k). Using segment data from the traffic files of Form 41 during the period 1995 – 2003 and defining three different network segments (point-to-point, hub-to-hub, and hub-to-spokes), we specified econometric models that attempt to capture the determinants of air traffic performance. Empirical results indicate that the specified model for the index^k has a reasonable fit.

Our results for the index^k model indicate that the sets of explanatory variables explain the air traffic performance particularly well for hub-to-hub and hub-to-spoke networks. Results indicate that busy times of the year affect air traffic performance negatively for two variants of the hub-to-spoke network segments (i.e., hub-to-hub and hub-to-spoke) and positively for the point-to-point network segment. Second, market size tends to positively influence performance for the hub-to-hub networks while it negatively influences hub-to-spoke and point-to-point network segments. Third, while the incidence of terrorism has enhanced the air traffic performance for the point-to-point network segment, it affected the hub-to-spoke network segment variants negatively. Fourth, distance seems to improve performance but at a slower rate. Fifth, while the presence of network carriers reduces performance, operations by Southwest Airlines improves it for all networks. Finally, the larger the size of aircraft, the poorer the performance.

These results have interesting policy implications. For example, our results demonstrate that hub-and-spoke networks may need long-term policy priorities in solving air traffic performance issues that characterizes busy periods. Second, there may exist some unused capacity within the hub-to-hub system of airports. Hence careful attention should be given to distinguish airports within the hub-to-hub network while planning for future airport capacity.

Appendix A:

Results for Point-to-Point Network

Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|	Variable Label
Intercept	1	0.7263	0.001073	676.74	<.0001	
dummy1	1	-0.002356	0.000592	-3.98	<.0001	season dummy: spring&summer=1; fall&winter=0
mktsize	1	-0.000781	0.000160	-4.87	<.0001	size of the market dummy: 0 is thinnest while 7 is thickest
Terrorism	1	0.007687	0.000658	11.69	<.0001	9/11 dummy (>=2001:Q3=1;else=0)
Avgdistance	1	0.000321	1.2215E-6	262.33	<.0001	average distance between market pair
avgdistancesq	1	-7.411E-8	4.915E-10	-150.80	<.0001	square of average distance
American	1	-0.0399	0.000978	-40.79	<.0001	American Airlines dummy
Continental	1	-0.0278	0.001059	-26.25	<.0001	Continental Airlines dummy
Delta	1	0.0188	0.000892	21.10	<.0001	Delta Airlines dummy
Northwest	1	-0.0179	0.000911	-19.61	<.0001	Northwest Airlines dummy
Southwest	1	0.0451	0.000919	49.05	<.0001	Southwest Airlines dummy
USAir	1	0.001773	0.000823	2.15	0.0312	USAir dummy
United	1	-0.0124	0.000930	-13.34	<.0001	United Airlines dummy
ACCategory	1	-0.0204	0.000270	-75.73	<.0001	Aircraft dummy
AR1	1	-0.1579	0.001605	-98.40	<.0001	
AR2	1	-0.0413	0.001619	-25.53	<.0001	
AR3	1	-0.0606	0.002097	-28.91	<.0001	
AR4	1	-0.0227	0.001661	-13.69	<.0001	

Results for Hub-to-Hub Network

Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|	Variable Label
Intercept	1	0.7112	0.001468	484.52	<.0001	
dummy1	1	-0.007952	0.000624	-12.75	<.0001	season dummy spring&summer=1; fall&winter=0
mktsize	1	0.001489	0.000144	10.37	<.0001	size of the market dummy. 0 is thinnest while 7 is thickest
Terrorism	1	-0.004599	0.000701	-6.56	<.0001	9/11 dummy (>=2001:Q3=1;else=0)
Avgdistance	1	0.000282	1.1635E-6	242.27	<.0001	average distance between market pair
avgdistancesq	1	5.755E-8	3.959E-10	145.34	<.0001	square of average distance
American	1	-0.0275	0.000922	-29.81	<.0001	American Airlines dummy
Continental	1	-0.0211	0.000936	-22.50	<.0001	Continental Airlines dummy
Delta	1	-0.0108	0.000841	-12.90	<.0001	Delta Airlines dummy
Northwest	1	-0.009301	0.000883	-10.53	<.0001	Northwest Airlines dummy
Southwest	1	0.0517	0.001385	37.33	<.0001	Southwest Airlines dummy
USAir	1	0.000404	0.000868	0.46	0.6421	USAir dummy
United	1	-0.003781	0.000818	-4.62	<.0001	United Airlines dummy
ACCategory	1	-0.0190	0.000301	-63.15	<.0001	Aircraft dummy
AR1	1	-0.1035	0.002035	-50.84	<.0001	
AR2	1	-0.0762	0.002040	-37.36	<.0001	
AR3	1	-0.0584	0.002041	-28.60	<.0001	
AR4	1	-0.0464	0.002033	-22.80	<.0001	

Results for Hub-to-Spoke Network

Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|	Variable Label
Intercept	1	0.7263	0.001073	676.74	<.0001	
dummy1	1	-0.002356	0.000592	-3.98	<.0001	season dummy: spring&summer=1; fall&winter=0
mktsize	1	-0.000781	0.000160	-4.87	<.0001	size of the market dummy: 0 is thinnest while 7 is thickest
Terrorism	1	0.007687	0.000658	11.69	<.0001	9/11 dummy (>=2001:Q3=1;else=0)
Avgdistance	1	0.000321	1.2215E-6	262.83	<.0001	average distance between market pair
avgdistancesq	1	-7.411E-8	4.915E-10	-150.80	<.0001	square of average distance
American	1	-0.0399	0.000978	-40.79	<.0001	American Airlines dummy
Continental	1	-0.0278	0.001059	-26.25	<.0001	Continental Airlines dummy
Delta	1	0.0188	0.000892	21.10	<.0001	Delta Airlines dummy
Northwest	1	-0.0179	0.000911	-19.61	<.0001	Northwest Airlines dummy
Southwest	1	0.0451	0.000919	49.05	<.0001	Southwest Airlines dummy
USAir	1	0.001773	0.000823	2.16	0.0312	USAir dummy
United	1	-0.0124	0.000930	-13.34	<.0001	United Airlines dummy
ACCategory	1	-0.0204	0.000270	-75.73	<.0001	Aircraft dummy
AR1	1	-0.1579	0.001605	-98.40	<.0001	
AR2	1	-0.0413	0.001619	-25.53	<.0001	
AR3	1	-0.0606	0.002097	-28.91	<.0001	
AR4	1	-0.0227	0.001661	-13.69	<.0001	

REFERENCES

Air Transport Association, 2004 See http://www.airlines.org/public/home/default1.asp.

Bhadra, D., 2004, "Air Travel in Small Communities: An Econometric Framework and Results," *Journal of the Transportation Research Forum*, vol. 43, no. 1, (pp. 19-37), Spring, 2004.

Bhadra, D. and P. Texter, 2004 "Airline Networks: An Econometric Framework to Analyze Domestic US Air Travel", paper (forthcoming) at the *Journal of Transporation and Statistics*, Sept-Oct., 2004.

General Accounting Office. 2002. *Commercial Aviation: Air Service Trends at Small Communities Since October 2000*, Report to Congressional Requesters, GAO Report No. GAO-02-432, Washington, D.C.

Bolczak, C. N., J.H. Hoffman, A.J. Jensen, and W.W. Trigeiro, 1997, "National Airspace System Performance Measurement: Overview, MITRE Technical Report (no. MTR97W0000035), McLean, Virginia: The MITRE Corporation.

Eurocontrol, 2000, *Aircraft Performance Summary Tables for the Base of Aircraft Data (BADA)*, Revision 3.3., EEC Note No. 18/20, Bretigny sur Orge.

FAA, 2004, "Capacity Needs in the National Airspace System: An Analysis of Airport and Metropolitan Area Demand and Operational Capacity in the Future," Washington, DC: US Department of Transportation, Federal Aviation Administration.

Cavcar, A. and M. Cavcar, 2004, "Impact of Aircraft Performance Characteristics on Air Traffic Delays", *Turkish Journal of Engineering and Environmental Science*, 28(2004), 13-23.

Dell'Olmo, P. and G. Lulli, 2002, "A New Hierarchical Architecture for Air Traffic Management: Optimization of Airway Capacity in a Free Flight Scenario," *European Jouranl of Operational Research*, 04-04.

Pindyck, R.S. and D. L. Rubinfeld, 1991, *Econometric Models and Economic Forecasts*, 3rd Edition, New York: McGraw-Hill, Inc.

SAS/ETS Software, 1993, Applications Guide 2: Econometric Modeling, Simulation, and Forecasting, Version 6, First Edition, SAS Institute.

Shy, O., 2001, *The Economics of Network Industries,* Cambridge, MA: Cambridge University Press.

U.S. DOT, 2001, *Code of Federal Regulations,* Ch II (1-1-01 Edition), Pt. 241, Washington, DC: Office of the Secretary, US Department of Transportation.

____. 1992. *O&D Survey Reporting Regulations for Large Air Carriers: Code of Federal Regulations Part 241, Section 19-7,* Washington, DC: Office of the Secretary, US Department of Transportation.